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DEVELOPMENT OF A NEURAL NETWORK MATHEMATICAL MODEL FOR DEMAND FORECASTING IN FLUCTUATING MARKETS

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ABSTRACT

Research has shown that Neural Networks (NNs) when trained appropriately are the best forecasting system compared to conventional techniques. Research has shown that there is no system to accurately forecast sudden changes in demand for a given product. This paper reports on the development of a recovery method when a sudden change in demand has taken place. This error in forecasting demand leads to either excessive inventories of the product or shortages of it and can lead to substantial financial losses for the company producing or marketing the product. Two recovery methods have been developed and described in this paper: RZ recovery and Exponential Smoothing (ES). In the RZ recovery once a sudden change has taken place, a 'soft' Poke-Yoke (PY) system is setup warning the company that the normal forecasting system can no longer be relied upon and a recovery system needs to be initiated, with re-forecasting initiated.

Keywords: forecasting, artificial neural network, exponential smoothing.

1 INTRODUCTION

The first task was to design an experiment to demonstrate that the RZ recovery would work and that it is a more accurate method of demand forecasting than the existing forecasting systems, in fluctuating periods, for demand for a product. In previous experiments it was shown that neural networks are the most accurate demand forecasting methods (Ziarati, 2003; Urkmez et al, 2007, 2008; Akdemir, 2007, 2008). In terms of accounting for recovery and taking account of past events it is known that ES techniques have been used in predicting demands in fluctuating markets with some success in the past. To this end, a conventional Exponential Smoothing (ES) system is applied to calculate the demand for the product during a fluctuation period in the market for a given product. The result has shown the RZ recovery is more accurate than ES techniques and this recovery system would help to address the sudden change in demand for given products and helps to make the inventory system more efficient ensuring that the excessive over supply or shortages for a given product are kept to a minimum. Once the market has settle down the PY would effectively stop the recovery system and automatically reconvene the normal forecasting operations. The development of dual forecasting system, Neural Network for general prediction of demand for products and the RZ recovery for sudden changes, is considered an innovative approach. Whilst the prediction has shown to be more accurate and the risk of significant possible errors reduced, the proposed system is still a forecasting model and reliability still an issue.

2 DESIGN OF EXPERIMENT

To design an experiment there was a need to identify a set of data which could be used to test the two recovery approaches. The main requirement in the design process was that the data chosen should have at least have a major sudden change in demand for a given product(s). As two of the authors are associated with shipping companies a decision was made to use the Baltic Exchange Dry Index (BDI) values for this investigation. BDI is a measure of capacity needs for various types of ships (World fleet Grand total). This data is organized monthly and it is shown in a graphical form in Figure 1. It contains the demand for ships from November 1999 to April 2009. The data for November to January 2000 has been used for training the NN.

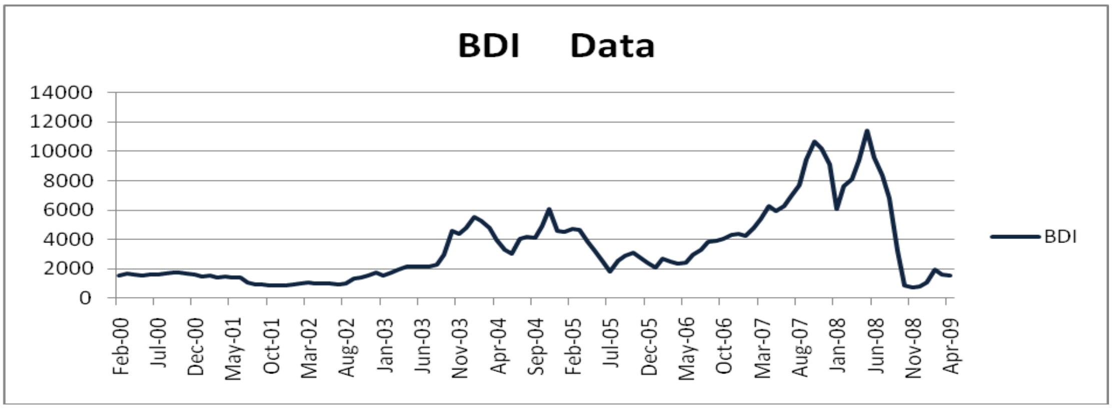

Figure 1: Baltic Exchange Dry Index

Forecasting BDI values three types of conventional methods were used: regression, exponential smoothing and NNs. There are many other techniques which in the majority of cases either rely on one of these techniques (or a variation) or a combination of them for example correlation, time series and so forth. There are several other methods such as percentage errors, probability methods, etc. A good account of these methods and their accuracy is given in Ziarati (2003).

In the majority of cases there is not sufficient data to predict accurately the future demand for a product or service. To this end, neural network systems have become more popular (Holland, 1975). However, the main reason for the popularity and recent prominence of neural networks is that they are basically learning mechanisms and are capable of handling a large amount of data and coming up with reliable outcomes provided the network is carefully constructed, trained and tested. This ability to learn 'seemingly large amount of abstract data and to interrelate different sets of information' makes them ideal tools for forecasting (Ziarati, 2003; Chua and Yang1988).

The theory of forecasting techniques including how the neural network works is fully described in Ziarati (2003). The purpose of the work presented here is to establish if methods used by Ziarati can be adapted to predict supply and demand for sea transportation (World Fleet Grand Total) and indexes such as BDI.

3 NEURAL NETWORK

The neural models are generally based on the perceived work of the human brain. The artificial model of the brain is known as Artificial Neural Network (ANN) or simply Neural Networks (NNs). The network is composed of large numbers of neurons and their intra-and inter-connections. The neurons operate collectively and simultaneously on most for all data and inputs which performs as summing and nonlinear mapping junctions. There is several kinds of neural network topology. Generally, the feed-forward multilayer neural networks topology and back-propagation training algorithm are commonly used for neural network applications.

Multi-layer ANN consists of multiple layers of computational units, usually interconnected in a feed-forward way. Each neuron in one layer has directed connections to the neurons of the subsequent layer. In many applications the units of these networks apply a sigmoid function as an activation function.

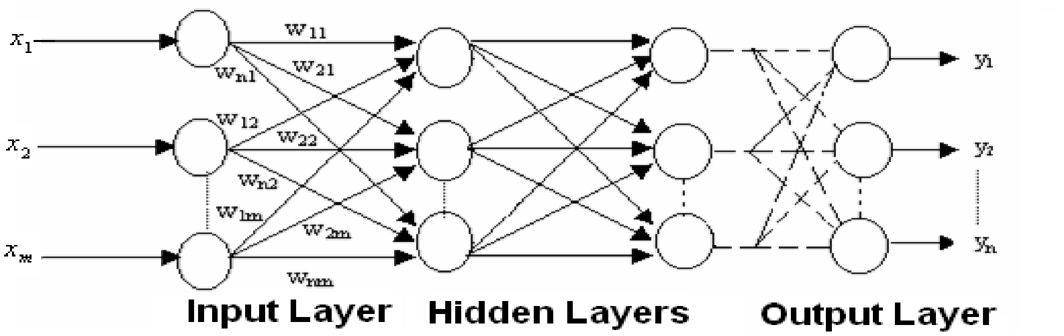

Figure 2: Multi- layer feed forward ANN

Multi-layer networks use a variety of learning techniques, the most popular being *back-propagation*. Here, the output values are compared with the correct answer to compute the value of some predefined error-function. By various techniques, the error is then fed back through the network. Using this information, the algorithm adjusts the weights of each connection in order to reduce the value of the error function by some small amount. In this research work, a multi-layered, feed forward neural network architecture with two hidden layers as shown in Figure 2. This neural network model has an extra hidden layer named pre-processing layer. It is allocated between the input layer and main hidden layer. In the input layer we have 17 neurons representing 4 independent variables, one dependent variable and 2 trend factors extracted from the independent variable. Historically, the last 3 values of each independent and the dependent variable were given to the neural network. In the first hidden layer, pre-processing layer, there are 10 neurons. In the second hidden layer there are 5 neurons. There are two outputs which are the predicted value of the total world dry bulk fleet and the validation value for representing the reliability of the results of the neural network.

It is expected that the neural network finds the relationships between the input parameters and the output parameters by adjusting its weights and biases. This neural network has three weight matrices and three bias vectors. Dimensions of the weight matrices and bias vectors depend on the architecture of the neural network. Here, U is a weight matrix with the size of 17 x 10 between the input layer and pre-processing layer, V is another hidden layer weight matrix with the size of 10 x 5 between the pre-processing layer and the main hidden layer and W is the last weight matrix with size of 5 x 2 between the main hidden layer and the output layer exist in this neural network structure. A number of the elements of the first weight matrix is decreased from 170 to 34 by choosing the proposed connection topology between the input layer and the pre-processing layer. It is supposed that, in a given time, the world fleet grand total value depends on its historical values and the historical values of the other independent variables. Forecasting results with ANN is shown in Figure 3.

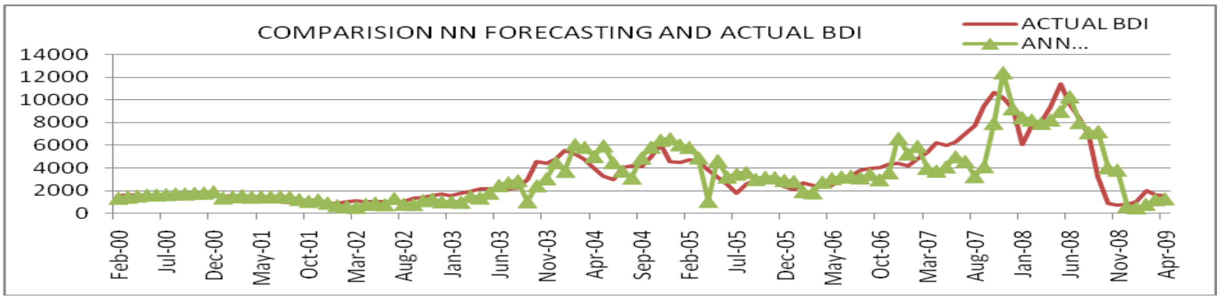

Figure 3: Forecasting with Neural Network

4 EXPONENTIAL SMOOTHING MODELLING

It is a very popular scheme to produce a smoothed time series. Whereas in Single Moving Averages the past observations are weighted equally, Exponential Smoothing assigns exponentially decreasing weights as the observations get older. Exponential Smoothing schemes weight past observations using exponentially decreasing weights. In other words, recent observations are given relatively more weight in forecasting than the older observations. In the case of moving averages, the weights assigned to the observations are the same and are equal to 1/N. Where N is number of observation. In exponential smoothing, however, there are one or more smoothing parameters to be determined and these choices determine the weights assigned to the observations. There are three exponential techniques commonly in use such as Single Exponential Smoothing (SES), Double Exponential Smoothing (DES) and Triple Exponential Smoothing (TES). In this study, all these three exponential smoothing techniques are reviewed and applied to BDI data forecasting as shown in Figure 4, and the results with RZ recovery technique is shown in Figure 5.

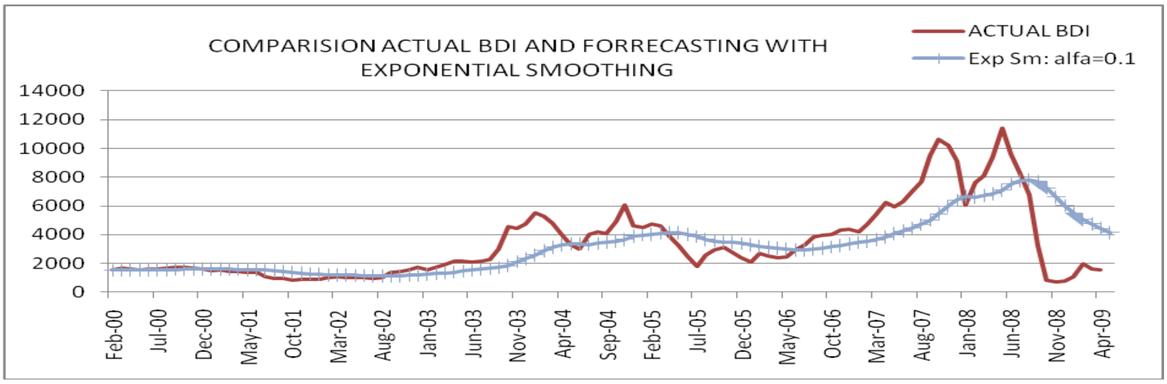

Figure 4: Forecasting Using Exponential Smoothing

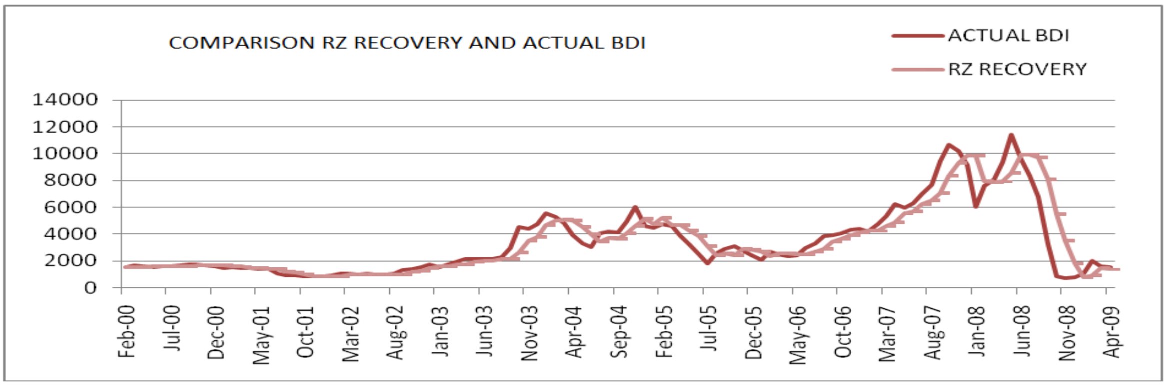

Figure 5: Forecasting Using RZ Recovery

4.1 Single Exponential Smoothing Model

For any time period *t*, the smoothed value S_t is found by computing;

$$S_{t+1} = \alpha y_t + (1-\alpha)S_t \qquad 0 \leq \alpha \leq 1$$

where S_t stands for smoothed observation, and y_t stands for the original observation. This is the basic equation of exponential smoothing and the constant or parameter α is called the smoothing constant. The subscripts refer to the time periods, $1, 2, \ldots, n$.

4.2 Double Exponential Smoothing Model

Single Smoothing (short for single exponential smoothing) does not take into consideration if effects of trend is required to be taken into consideration as there is only one single coefficient α. This situation can be improved by the introduction of a second equation with a second constant γ, which must be assigned in conjunction with α. Here are the two equations associated with Double Exponential Smoothing:

$$S_t = \alpha y_t + (1-\alpha)(S_{t-1} + b_{t-1}) \qquad 0 \le \alpha \le 1$$

$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)\, b_{t-1} \qquad 0 \le \gamma \le 1$$

Note that the current value of the series is used to calculate its smoothed value replacement in double exponential smoothing. There are a variety of schemes to set initial values for S_t and b_t in double smoothing. S_1 is in general set to y_1. The first smoothing equation adjusts S_t directly for the trend of the previous period, b_{t-1}, by adding it to the last smoothed value, S_{t-1}. This helps to eliminate the lag and brings S_t to the appropriate base of the current value. The second smoothing equation then updates the trend, which is expressed as the difference between the last two values. The equation is similar to the basic form of single smoothing, but here applied to the updating of the trend. The one- and m- period-ahead forecast is given by:

$$F_{t+1} = S_t + b_t \;, \quad F_{t+1} = S_t + mb_t$$

4.3 Triple Exponential Smoothing Model

If the data include trend and seasonality then double smoothing will not be effective. To this end, a third equation will have to be introduced to take care of seasonality (sometimes called periodicity). The resulting set of equations is called the "Holt-Winters" (HW) method after the names of the inventors. The basic equations for their method are given by:

$$S_t = \alpha \frac{y_t}{I_{t-L}} + (1-\alpha)\,(S_{t-1} + b_{t-1})$$
$$b_t = \gamma(S_t - S_{t-1}) + (1-\gamma)b_{t-1}$$
$$I_t = \beta \frac{y_t}{S_t} + (1-\beta)I_{t-L}$$
$$F_{t+m} = (S_t + mb_t)I_{t-L+m}$$

Where y is the observation, S is the smoothed observation, b is the trend factor, I is the seasonal index, F is the forecast at m periods ahead and t is an index denoting a time period. α, β and are constants that must be estimated in such a way that the MSE of the error is minimized. To initialize the HW method we need at least one complete season's data to determine initial estimates of the seasonal indices I_{t-L}. A complete season's data consists of L periods. The trend factor also needs to be estimated from one period to the next. To accomplish this, it is advisable to use two complete seasons; that is, 2*L* periods. All results with the techniques mentioned such as ANN, ES and RZ recovery shown in Figure 6.

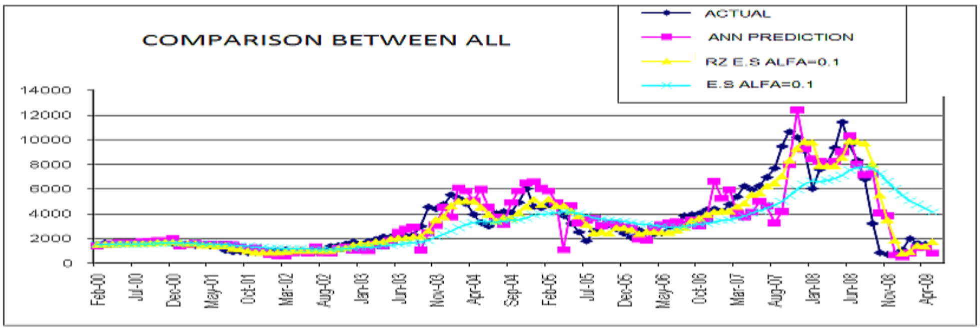

Figure 6. Forecasting with Triple Exponential Smoothing

5 CONCLUSIONS

When there are sudden changes in demand for a given product, this sudden change should be identified using a form of a PY and corrective action should be taken while abnormal fluctuations are taking place. In this experiment a PY system was introduced and two distinct corrective action methodologies, one based on ES and the other one on the RZ recovery were presented. The advantage of recovery system is that in addition to offering a mechanism for correcting demand forecast it provides an opportunity to make the necessary corrections to inventory of the product. One other benefit is that the inventory is taken into consideration when computing the forecast demand for the product. There are no recovery systems for when sudden change in demand are noted for a given product. It is a known fact that exponential smoothing takes account of past changes and this offers some corrective measures when forecasting demand for a product.

The RZ recovery, using the neural network mathematical model described in this paper as shown in Figure 6, by taking account of the last three actual data for any demand forecasting, proved to be more accurate than the very best of ES techniques.

This study has led to a successful outcome. Considering the results, it can be concluded that it is possible to identify a sudden change in the market for given product and have an effective software method for a corrective/recovery system for a more accurate prediction of demand for a given product. The RZ recovery system also allows inventory for the product to be continuously amended so that only the minimum numbers are produced after each demand forecast.

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